A Multiple Objectives Optimization Approach To Robotic Teams' Analysis, Design And Control

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Abstract *An optimization approach to distributed intelligent system design and control is presented. It is expected to enhance the autonomous decision-making capabilities of subsystems. It is applicable to autonomous multiple agents homogeneous or heterogeneous clusters, when they must collaborate to achieve a common goal, acting in a coordinated manner that will provide situation awareness, collision avoidance and operations in complex environment and degraded communications or sensors failures.*

1. Introduction

I propose a new, multiple objectives optimization based approach to distributed intelligent system design and control which will lead to an improved performance of many missions by enhancing the autonomous decision-making capabilities of subsystems. It is applicable to autonomous multiple agents homogeneous or heterogeneous clusters, when they must collaborate to achieve a common goal, acting in a coordinated manner that will provide situation awareness, collision avoidance and operations in complex environment and degraded communications or sensors failures. It is designed to operate in real-time, with no single agent indispensable to the process and with self monitoring of execution and recovery from faults. Hierarchical, multi-resolution approach provides coordination among the levels of control within a distributed architecture. Modularity of design enabling advanced debugging and model-development environments for autonomy software.

2. The Problem

At present, there is no consistent mathematical theory for the automated reasoning, control and design of large set of intelligent subsystems which must compete, collaborate or even just share some space or resources. As a result, a "suboptimal", often ineffective, heuristics based design 'rules' are used, leading to the well known unreliable, poorly scalable, and brittle behavior of these systems.

For example, how does one design and execute the control, resources allocation and coordination of a group of independent agents/robots/systems? What are the underlying principles for the "decentralization" of the design, communication and control of these systems?

Our proposed approach will attempt to offer a solution to these problems, which indeed are highly generic. Many communications, networking, software development, system management and many other important engineering tasks fall under this class of problems.

3. Approach

On the basis of several observations which we make regarding such systems, a new constructive definition of COOPERATING/TEAM of systems will be offered. Then, in a rigorous manner, the tools of Multiple Objective Optimization (MOO) [3], (as well as, mathematical programming, dynamic systems control, differential games and other theories) – will be employed to generate a mathematical theory, which we name <u>MOO Approach</u>. We shall then proceed with the design of a set of algorithms, for the design, analysis and control of distributed intelligent systems. Such MOO Approach is the framework that embodies well-defined architectural concepts for enabling the development of autonomous systems that meet high level mission goals.

4. Background and Approach

How does one distinguish between a group of agents and one "complex" agent? This question is <u>central</u>, since without such distinction, there is no "hope" for obtaining scalable, distributed algorithm, in order to improve upon the present state of the art solutions offered by large scale system design. Present approaches do not distinguish between a large scale dynamic system obtained as an aggregate of the agents subsystems (with augmented dynamics and state space) – and a set of dynamic systems, describing each agent that, though coordinated, are independently controlled, while sharing state space subset or other constraints. As a result, sub-optimal, often ineffective resources utilization via heuristics based approaches are employed and much confusion exists in the terminology used, in the communication of research and engineering results and in the technology transfer and deployment.

Furthermore, what makes a system a whole (unique, as in "one"), is the fact that there is a __**unique**__ **function/task/objective to be shared by all its components. In the case where, various subsystems (of the said system) have different, i.e., non-redundant, non-overlapping objectives/tasks/missions/constraints – we no longer are dealing with a single system but rather with a set of systems, which may or may not be coupled.**

Note - All systems have at least one (often implicit) objective/task. Examples: - maximize survivability; minimize metabolism/energy used; minimize time.

__**Proposed Definition**__**: A COOPERATIVE/TEAM OF SYSTEMS is a set of systems for which, in addition to the original individual objectives of each system member, the group/team jointly possesses a common objective.**

Thus a system becomes a member of a team of systems, only by "accepting" an additional objective ("commitment") – that of the team's task! Such team objective is normally and often, contradictory to (conflicting with) the "self" objective of the member system.

__**Mathematical Basis and Benefits of MOO Approach**__

Dynamic systems theory and multiple objective optimization theory may be employed in the planning, design and control of A COOPERATIVE SYSTEM as follows:

1. For each i-th Agent/member System (i-th member of the set), let: Xi be the system's state vector, Ui be the systems input; Yi be the systems output; fi(Xi,Ui,t) be the system's dynamics; Oi be the system's performance index (objective function).

2. Let U=Union(Ui) be the augmented input vector; X=Union(Xi) be the augmented state vector; Y=Union(Yi) be the augmented output vector, and f= Union(fi) be the augmented system dynamic.

3. Let O be the team of system's objective/performance index functional defined on the augmented state and input space {X,U}.

4. Let Gj(X,U)<=0 be the set of input and state inequality constraints, describing obstacles (generalized, including the space occupied by other systems in the team); hardware limits; boundaries etc. __**Notice that G and O are the only source of coupling in this augmented system!**__

__**Control of a COOPERATIVE, an Example**__ **(see [1] for solution approach)**

The problem of control of a team of systems may be stated as follows: Find the input U (as a feedback control law or as an open loop profile) which simultaneously minimizes the Objective functions set: {U; Ui, I=1,2,,,,), subject to the dynamics f, the constraints G and the boundary conditions: X(t0) (initial given state); X(tf) (final desired state).

__**Outline of the MOO design**__: Since the only source of coupling is through the inequality constraints G and the common objective function O, a solution may be sought as follows:

1. Project O and G on the i-th state space and obtain the corresponding restricted constraints and objective functions for each i-th subsystem

2. For each i-th subsystem, independently and simultaneously solve the resulting multiple objective optimal control problem. See [2,3,4] for a detailed solution for a linear time invariant case. **Such a "solution" consists of identifying the set of non improvable decision variables, the so called - Pareto set, which encompasses all the optimal tradeoffs which the i-th system may choose in compromising its self objective with that of the team and vice versa. The Pareto set may or may not be a connected set. The Pareto set is the key source of many of the expected benefits of the proposed approach. Since the total design is reduced to N simultaneous and independent Pareto sets - is vastly smaller then the set of design alternatives which present approaches of distributed intelligence, where we obtain one N dimensional Pareto set, and which it must search and consider.**

3. The solution of our problem is obtained as the aggregate control U consisting of all of the corresponding Ui solutions as obtained in step 2 being selected from their corresponding Pareto sets.

5. Important Features/Objectives Of The Moo Approach

Due to the underlying mathematics involved in the MOO Approach as described above, the resulting distributed system is expected to possess the following features:

D1. Decentralized/Parallel/Distributed Design Control and Communication. This is due to the fact that each subsystem is independently optimizing (planning) and executing its tasks. Notice that this benefit is both in the hardware as well as the software structure aspects of the design.

D2. Linear Scalability Notice that, unlike present centralized, large scale system design [5] and/or current distributed (e.g. Neurocontrol) [6] control/communication architectures, which scale geometrically in the aggregate system dimension (as measured by the number of subsystems), the MOO approach is expected to scale linearly!

D3. Maximal Delegation/Autonomy. This is expected since each subsystem communicates with team members normally only through its onboard sensors (via the environment in which the entire team operates, and not through peer to peer channels. Also, since the only information downloaded from higher levels, is the teams task objective (i.e., higher level information and not detailed planned trajectories, the i-th system need not be informed about the tasks and plans of other systems) – there communication burden is reduced and maximal autonomy is delegated.

D4. Robustness and Reliability. With reduced complexity we expect improved robustness. For example when a sudden cost is being observed at the i-th system Pareto set, it implies some failure or structural change, which will result automatically in some other system, say the j-th to select a different point in its own Pareto set since its payoff will increase. Note that such fault detection and recovery occurs without centralized re-planning

D5. Hierarchical and Multi Resolution Design It is possible to apply the MOO approach to several resolution system levels and to provide coordination among the levels of control within a distributed architecture. This will enable:

D6. **Modularity** of design enabling advanced debugging and model-development environments for autonomy software. **Easily and inexpensively programmed and modified due to their modular and invariant structure. Also, easily and inexpensively maintained and trained due to their modularity and invariant structure**

D7. Optimal Performance. The essence of this approach.

These MOO Approach properties (D1 to D7) are expected to provide: high performance, with dramatically lower complexity, D2 and D3, and reduced resource consumption intelligent and reflexive behavior. Also D1, implies a naturally distributed architectures for autonomy with automatic coordination, which includes multiple types of autonomous agents, or mixed human-artificial agents. We can also expect intelligent fault protection (D4), providing model-based fault management capabilities into an autonomous executive control loop. For example when a sudden cost is being observed at the i-th system Pareto set, it implies some failure or structural change, which will result automatically in some other system, say the j-th to select a different point in its own Pareto set since its payoff will increase. Note that such fault detection and recovery occurs without centralized re-planning. Due to D7, planning and execution are done via real time optimization, which is viewed as automatic planning and execution, generating sequences of executable activities, as well as systems for robust execution. Indeed these are large-scale concurrent planning under uncertainty involving continuous quantities such as time and resources.

6. Examples

Description of the MOOP demonstration simulation

This document describes the simple simulation program that is used to demonstrate the MOOP approach to Distributed Systems control problem.

Let the global task to be motion from initial position to terminal position in the plane (ξ, y), be described by:

$$\begin{bmatrix} \xi_g(t) \\ y_g(t) \end{bmatrix}, t_0 \leq t \leq t_f$$

Let the position of each of the participants (robots) be described by the differential equation:

$$\begin{aligned}\dot{\xi}_{ri}(t) &= A\xi_{ri}(t) + Bu_{xi}(t), \xi_{ri}(t_0) = \xi_0, \\ \dot{y}_{ri}(t) &= Ay_{ri}(t) + Bu_{yi}(t), y_{ri}(t_0) = y_0,\end{aligned} \quad i = 1,2,3,...N.$$

where N- number of robots

we denote

$$x = \begin{bmatrix} \xi \\ y \end{bmatrix}.$$

Let

(i) the global(collaboration/tracking) task objective/cost of each robot be

In the research this cost will be express as the projection of the global task, defined on the augmented state space (see the proposal document), onto the local state space for each robot. This function will be based on the available measurement of the neighboring robots states. For example: leader's state, center of gravity of the formation; all the robots that are within some range, etc

$$J_{gi} = \int_{t_o}^{t_f} [x_{ri}(\tau) - (x_g(\tau) - d_i)]^T Q_{gi}[x_{ri}(\tau) - (x_g(\tau) - d_i)]d\tau, i = 1,2,3...N.$$

(ii) the self (survival/stabilization) cost of each robot be

$$J_{si} = \int_{t_o}^{t_f} x_{ri}(\tau)^T Q_{si} x_{ri}(\tau)d\tau, i = 1,2,3...N.$$

(iii) the energy expenditure cost (minimization of the effort)

$$J_{ei} = \int_{t_o}^{t_f} u_i(\tau)^T R_i u_i(\tau)d\tau, i = 1,2,3...N.$$

Each of the robots has its local objective that is trying to minimize locally

$$J_i = \alpha_i J_{gi} + (1-\alpha_i)J_{si} + J_{ei}$$

α_i - is controlled by higher levels of the hierarchy in order to specify the level of commitment of the i-th robot to the team i.e., the tradeoff between the global cost and self cost.

In the formulation above there is collaboration through the simultaneous measurement of all robots of the state of the execution of the tasks (where coupling might occur and through obstacle avoidance and constraints satisfaction (again where coupling might occur). Indeed it is the minimal amount of information and communication needed for collaboration and it is the KEY advantage of proposed approach!. Each of the participants is performing his decision based only on a strictly local pattern (notice that local info may contain possibly several robots states!):

The information pattern is: knowledge of the global task and knowledge of the local state. Thus the robot is weighting the global task with its own self-survival task. This is the minimal horizon collaboration pattern.

In this information pattern the collaboration is at a level that each robot knows the global task and tries to perform it irrespective of the performance of the others.

In order to introduce some collaboration into the structure we will assume that each robot has information on the location robots in its limited neighborhood. This is the Limited horizon collaboration pattern. It is a local pattern, as each specific robot does not have the information of all robots. The distributed structure is preserved as each robot decisions for are only based on limited information.

Notice that by providing more sensors and communication bandwidths to the robots –adding complexity and possibly improving performance

In order to demonstrate such pattern we form the following information pattern.

A leader is selected. Each of the robots knows the location of the leader and his position in the formation. The decisions are taken locally and the objectives are

the objective of the leader (i=1) is

$$J_{g1} = \int_{t_o}^{t_f} [x_{r1}(\tau) - x_g(\tau)]^T Q_{g1}[x_{r1}(\tau) - x_g(\tau)]d\tau.$$

and the objectives of the rest of the robots(i=2,3) are

$$J_{gi} = \int_{t_o}^{t_f} [x_{ri}(\tau) - (x_{r1}(\tau) - d_i)]^T Q_{gi}[x_{ri}(\tau) - (x_{r1}(\tau) - d_i)]d\tau, i = 2,3.$$

Thus the robots are tracking the leader. If the leader decides (locally) that he prefers self-survival cost at the expense of the global cost. The rest of the robots will keep with the leader thus preserving the formation. This formation preserving property has

been created by the Limited horizon collaboration pattern.
The collaboration level in this pattern is higher, as it dictated the global task will be performed at the leader "pace".

Different information patterns will create different collaboration patterns.
The Zero horizon collaboration pattern does not have formation preserving property.

In the examples the following simple collaboration patterns and their combinations are demonstrated:

(a) Follow the closest in front of you in the direction of the global task. If nobody is in front of you, within your horizon, you are the leader, and follow the global task.
(b) Self preservation at the cost of formation preservation
(c) Collision avoidance.

The mathematical description above is not a rigorous description of the simulation that are used in simulations used to the derive the following examples.

Examples:

Figures 1 and 2 describe the performance of the first collaboration pattern (1) (Follow the closest in front of you in the direction of the global task). The leader is selected randomly as the initial conditions of each the robot are random. Figure 1 is presented with high level of commitment for the formation creation (a_i=1). There are 20 robots in the example. Each robot is keeping the closest robot at 2o'clock direction and 5meter distance. Figure 2 presents the same 20 robots but with no commitment to formation (a_i=1). One can see that although the global task is fulfilled there are collisions. For $0<a_i<1$ different formations will be created.

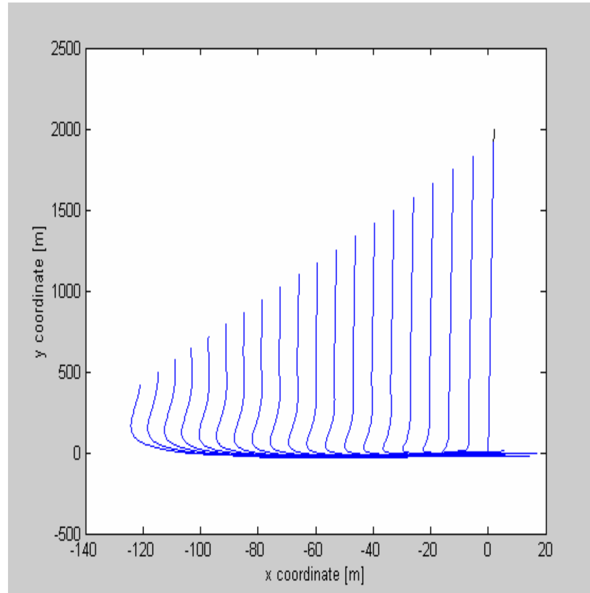


Figure 1: Formation creation with high level of commitment, a_n = 1, for 20 robots.

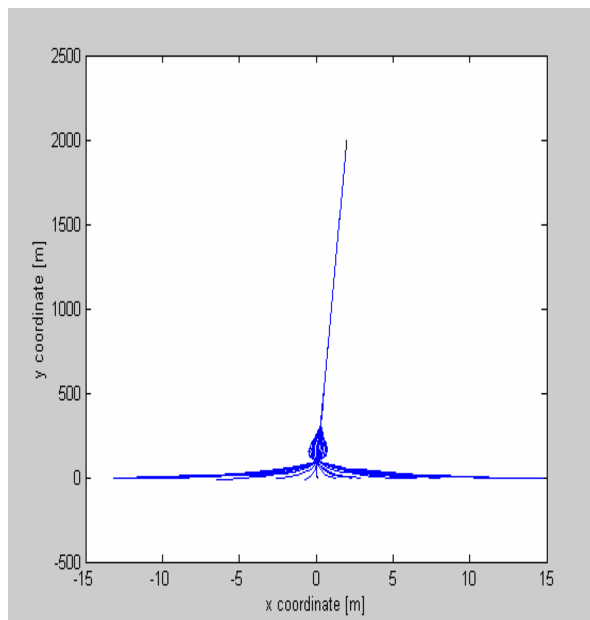
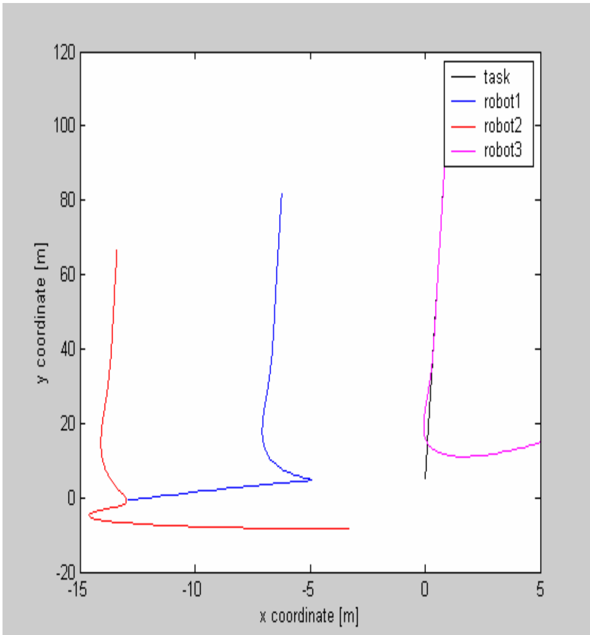
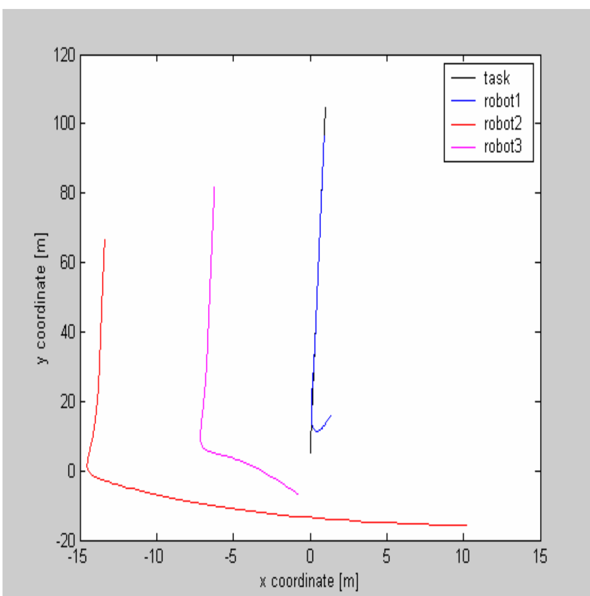


Figure 2: Formation creation with no commitment, a_n = 0, for 20 robots.

In order to show some additional features of the distributed MOOP approach we present some examples with only three robots. Figures 3 and 4 are presenting the same example but with different initial (randomly chosen) initial conditions. One can see that the leader has been selected randomly. Figure 5 show s an example when there is no commitment to formation. Figure 6 shows when there is a middling commitment to formation.



(a)



(b)

Figure 3: Formation creation with high level of commitment, a_n = 1, for 3 robots. Different initial positions.

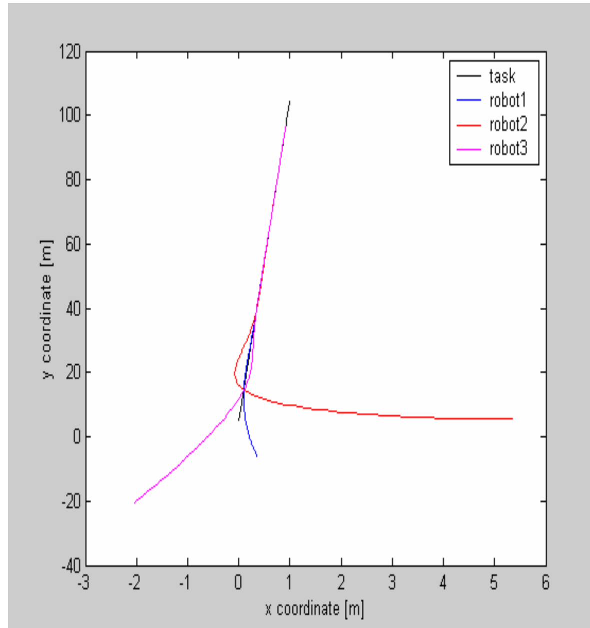


Figure 4: Formation creation with no commitment and no collision avoidance, $a_n = 0$, for 3 robots.

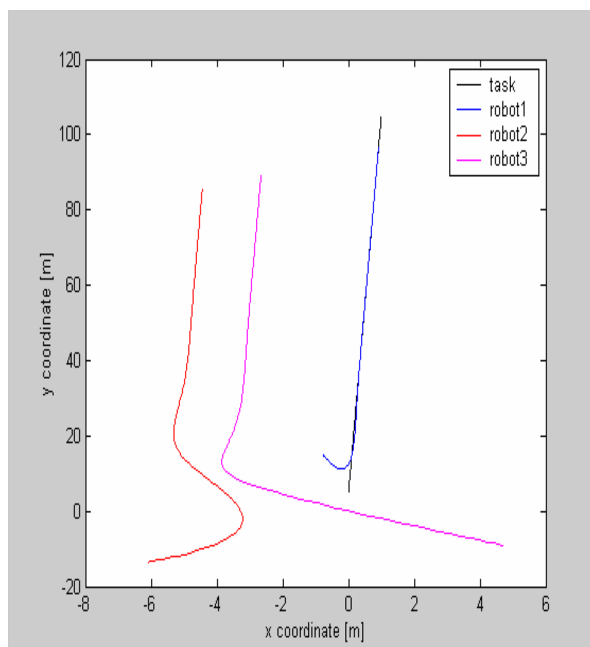


Figure 5: Formation creation with middling commitment, $a_n = 0.5$, for 3 robots.

Figure 6 presents the case when only self preservation is the sole objective at the expense of no global task tracking.

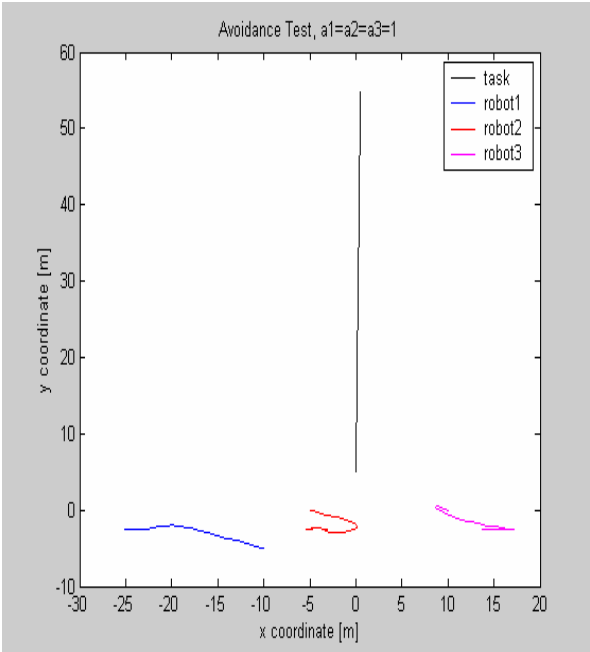


Figure 6: Behavior with no global task tracking commitment (only self preservation objective).

Figure 7 presents the case when formation is achieved with by global tracking commitment and collision avoidance this is achieved with middling weighing, a_i= 0.5, between global task tracking and collision avoidance. There is no leader in this case.

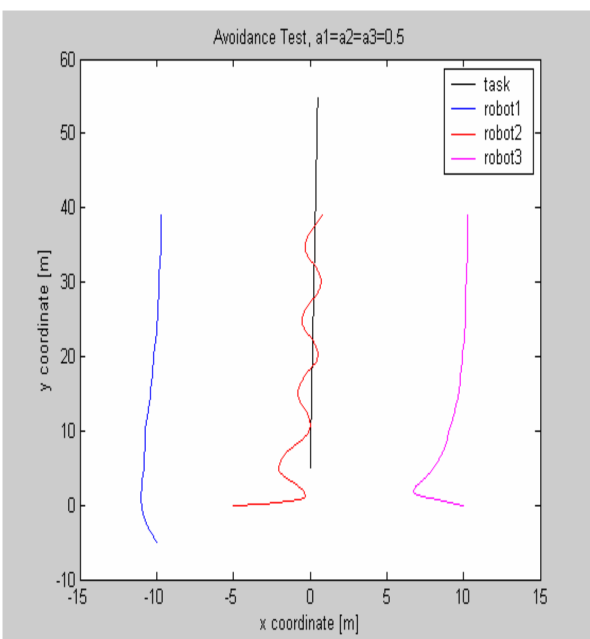


Figure 7: Middling tracking and avoidance, a_i= 0.5.

7. Discussion

I proposed a MOO based approach to distributed intelligent systems - analysis, design and control. Future publications will describe the results of applying this approach to design, management and control of complex systems.

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